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Research on Power IoT System Based City Block Air Pollutant Emission Prediction

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Abstract. In order to constantly improve city environmental air quality, it is necessary to accurately control the major pollutants emissions such as air fine particulate matter. By adopting the proposed iterative update framework of air pollutant emission inventory, combined with block-level real-time electricity consumption data acquired by the smart city power IoT, and utilizing station-level and hourly environmental air quality monitoring data in specific areas of Yuxi and Dali in Yunnan Province from 2020 to 2021, the iterative update of emission inventory and prediction of air pollutant emission are studied. The experimental results shows that the prediction of the monthly average major air pollutants emissions such as NO2/PM10/PM2.5 in specific neighbourhoods of the two cities mentioned above reaches the same accuracy level as using numerical simulation prediction methods, but the prediction computational power requirements are greatly reduced, making it more suitable for the application requirements of the power IoT. This study provides a new idea for improving the regulatory capacity of intelligent environment and achieving higher urban air quality based on the smart city power IoT.

1 Introduction

With the rapid development of human society, all countries are facing great challenges in air pollution and governance [1]. Air pollution refers to the phenomenon that some certain pollutant enters the atmosphere due to human activities or natural processes, and then the pollutant reaches a harmful level that damages the ecosystem and human's normal survival and development [2], and finally hurt the people or the things. Its essence is that atmospheric pollutants cause adverse effects on human's health and living environment through a series of complex physical, chemical, and biological processes [3].

Since China joined the WTO in 2000, the process of industrialization and urbanization has been accelerating. The scale of the secondary industry has been continuously expanded, and the number of cars has grown rapidly, leading to serious impact on environmental air quality management [4]. Since 2010, China's air pollution prevention and control work has experienced a long-term battle. The main monitoring objects are PM2.5 and PM10, gradually VOCs and O_3 are attracting attention, tending to achieve the balance of emissions and environmental quality protection, devoting to comprehensive control of multiple pollution sources and coordinated emission reduction of multiple pollutants [5-6]. The "14th Five Year Plan for Ecological Environment Protection in Yunnan Province" in 2022 [7] clearly states that there is still a long way to go to improve air quality, since the characteristics of industrial structure are difficult to change in a short time, and coordinated governance of PM2.5 and O_3 need to strengthen. It also pointed out that it is necessary to rely on the comprehensive improvement of intelligent environmental supervision to promote the goal of achieving urban air quality improvement.

This paper studies the formation mechanisms of environmental air quality issues, an iterative update framework for air pollutant emission inventory is adopted based on statistical methods and regression models [8], combines block-level real-time electricity consumption data collected by the smart city power Internet of Things. By utilizing corresponding regional station-level and hourly environmental air quality historical data, a fine-grained emission inventory that can be used to predict air pollutant emissions is iteratively updated, and used for predicting block-level air pollutant emissions. It not only effectively reduces the computation power requirements for predicting air pollutant emissions, but also provides great support for fine-grained and precise control of environmental air quality.

The main innovations and contributions of this paper are as follows.

a. The iterative updating framework of the air pollutant emission inventory is firstly adopted to predict

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air pollutant emissions based on the activity level of electricity consumption data.

b. By comparing and analysing the hourly observed data and predicted data of specific national monitoring stations in specific regions of Dali and Yuxi in Yunnan Province from 2020 to 2021, the applicability of the block-level air pollutant emission prediction method based on the power IoT is studied, and the relevant factors affecting the prediction results are summarized.

The remaining parts of this paper are organized as below: Section II introduce the related work. Section III propose the prediction algorithm based on iterative update framework of air pollutant emission inventory. Section IV research the prediction algorithm proposed in the previous section using hourly observed data from national monitoring stations in specific regions of Dali and Yuxi, as well as real-time electricity consumption data collected from the power IoT in specific regions, to verify its effectiveness and analyse the influencing factors of its applicability. Finally, discuss future research improvements and summarize the paper.

2 Related work

In order to achieve stable and standard air quality in urban environments, air quality prediction is the fundamental technical means. Air quality prediction technology methods can predict the concentration of atmospheric pollutants in regional space in advance, mainly including air quality model numerical simulation prediction methods [9-10] and prediction methods based on statistical models and artificial intelligence technology [11-12].

Research on predicting air pollutant emissions with different spatial accuracies has been carried out for many years [13-24].

In a type of study using numerical simulation prediction methods [13-19], the spatial areas covered by the input model emission inventory are rarely refined to the urban block level, and the prediction results are often evaluated at the provincial level [18], urban level [13,15-17,19], or urban level spatial granularity [14]. Reference [13] proposes to use the monthly electricity marketing data of enterprises to optimize the monthly time distribution coefficient of traditional air pollutant emission inventory based on product production. The monthly time spectrum in the basic emission inventory of corresponding enterprises in Tangshan City is replaced, and the optimized emission inventory is substituted into the CMAQ model for simulation to predict the air pollutant emissions in corresponding areas of Tangshan City, and verify the optimization effect of the prediction through parameter tests such as correlation coefficients with the monitoring values of national monitoring stations. Reference [14] uses the comprehensive forecast scoring method based on IAQI and the accuracy of grade levels, and uses the WRF-CMAQ model to carry out the numerical forecast simulation of air quality in the six districts of Beijing for different grid resolutions. Data analysis shows that in the long time series forecast, the resolution model with larger coverage area has better prediction effect, and the same station has different prediction effects on different resolutions. References [15-19] all used numerical models such as CMAQ and WRF-CHEM to predict the emissions of atmospheric pollutants such as PM2.5, PM10, and O_3 in Chinese cities Xi'an [15], Guangzhou [16], Shanghai [17], Jiangsu Province [18], and Italian cities Milan and L'Aquila [19].

In another kind of research based on statistical models and artificial intelligence technology prediction methods, historical data modeling and in-depth learning [23-24] prediction methods of meteorological characteristics (temperature, pressure, humidity, wind direction, wind speed, etc.) are usually more concerned. The prediction results are also mainly applicable to provincial, urban or urban spatial granularity. Reference [20] established a multiple regression model based on statistical methods for PM2.5 and temperature, wind power, meteorological factors, and conventional pollutants based on daily average observation data in Nanjing and Jilin cities in 2014. Through simulation and prediction, it was found that PM2.5 is correlated with wind power, weather, temperature, CO, NO_2, PM10, SO_2, and other factors, with CO concentration showing a significant correlation with PM2.5 concentration. Reference [21] studied the problem of PM2.5 concentration prediction in Shunde District, Foshan City, Guangdong Province. An air quality prediction model was established using a combination of clustering and multiple regression methods. Based on monthly and meteorological factor data, the daily average concentration of PM2.5 was clustered, and corresponding expressions were established for each class. The regression equation was used for prediction, and the predicted values and trends were close to the true values. The same method was used to predict the daily maximum 8-hour concentrations of NO_2, SO_2, CO, PM10, and O_3, all achieving good prediction results. Reference [22] studied the prediction problem of PM10 concentration in Tehran, Iran, and proposed a model that combines BP neural network and genetic algorithm, and used genetic algorithm to calculate the initial weights of the BP neural network to improve prediction accuracy. Reference [23] used a hybrid deep learning model to predict and analyze PM2.5 values in Beijing. Firstly, CNN was used to extract features from the input data, and then LSTM was used to predict and analyze the extracted features. Its performance was superior to traditional single deep learning models. Reference [24] also used a model combining CNN and LSTM to predict PM2.5 values in Beijing. The prediction performance was superior to traditional machine learning and deep learning algorithms when inputting past 24-hour values and outputting predictions for the next 1 hour.

The above research cannot meet the requirements of fine air quality supervision in smart cities to block level spatial granularity. It is urgent to combine the above research with the latest information technology methods such as the Internet of Things for power and use distributed methods to collect and predict data using IoT nodes, reduce the computational power requirements of prediction methods, improve the spatiotemporal accuracy of prediction results, and effectively support the application needs of various smart cities.

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3 Prediction algorithm based on Iterative update framework of air pollutant emission inventory

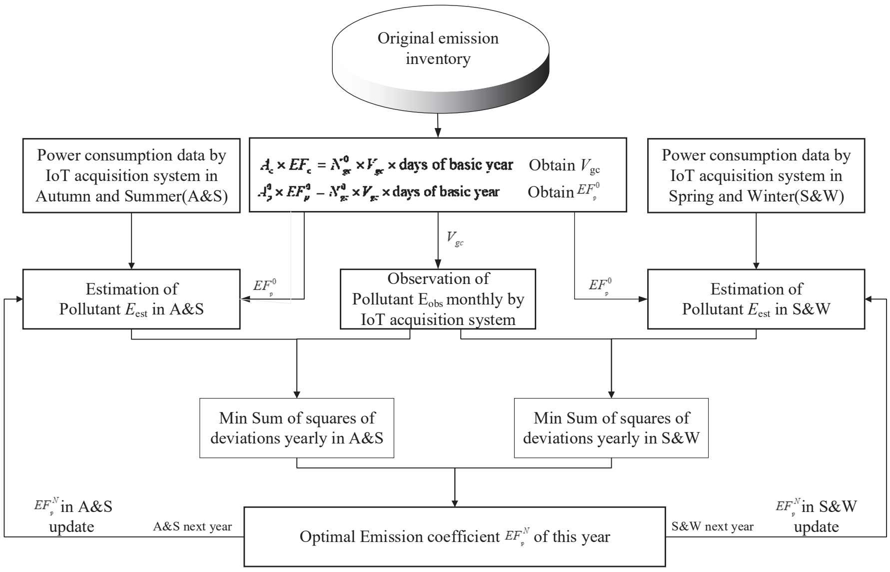


Fig. 1. Iterative update framework of air pollutant emission inventory based on activity level of electricity consumption data[8].

Through the proposed emission inventory iterative update framework [8], prediction algorithm is realized.

Relying on the IoT intelligent and sense terminal deployed by National Key Research and Development Program, a power IoT supporting intelligent energy application is formed to collect the block-level (1Km × 1Km) real-time electricity consumption data and air quality data. Using the proposed emission inventory iterative update framework [8], the emission coefficient of electricity consumption data based on the measurement of electricity activity level is continuously iteratively optimized based on terminal acquisition data. The block-level electricity consumption data is applied to predict the block-level air pollutant emissions. The prediction algorithm is shown in Figure 1 [8].

The process is as follows:

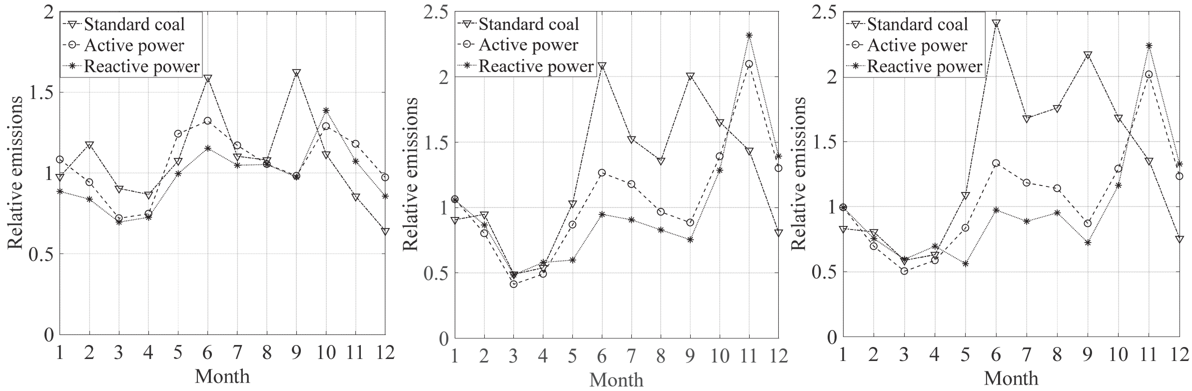
Firstly, set the initial values of the original emission inventory, and iteratively update the estimated pollutant value based on the observed station-level and hourly air pollutant concentration in spring, summer, autumn, and winter, as well as block-level electricity consumption data obtained from the power IoT. By calculating the deviation cost function based on the deviation between the observed and estimated values, the optimal estimation value is solved. According to the optimal estimation value of air pollutant, the emission coefficient of electricity consumption data is iteratively updated to form the next-round emission inventory, substituted into following calculation, achieving block-level air pollutant emission prediction, which can refers to reference [8] for specific algorithm design.

4 Experimental research on algorithm applicability

Research has shown [11-12] that using statistical models as the basis for predicting atmospheric pollutant emissions can be applied to smaller spatial areas, but there is a close relationship between predictive performance and meteorological factors in the predicted area. This article uses the proposed block level air pollutant emission prediction algorithm and electricity consumption data obtained from two similar enterprises in Yuxi and Dali, Yunnan from 2020 to 2021. The monthly average of NO_2, PM2.5, and PM10 emissions in their respective blocks are calculated using the proposed prediction algorithm and compared with the observed values at national monitoring stations to evaluate the applicability of the algorithm.

4.1. Applicability research of enterprise A in the block of Yuxi

Obtaining hourly electricity consumption data of a certain enterprise A in Yuxi from 2020 to 2021 through power IoT, using our proposed emission inventory iteration update framework [8], the electricity consumption data emission inventory iteration update was carried out, and the effective diffusion range (3km) of nearby national monitoring stations (2.6km away from enterprise A) in enterprise A was calculated. Therefore, the hourly observation data of the national monitoring station from 2020 to 2021 were selected as the training dataset (2020) and the evaluation dataset (2021).



(a)NO_2 (b)PM10 (c)PM2.5

Fig. 2. Comparison of Relative Values for Monthly Average Emission Prediction of Various Pollutants (NO_2 (a), PM10 (b), PM2.5 (c))

Table 1. Evaluation indicators for monthly average prediction results of pollutant emissions.

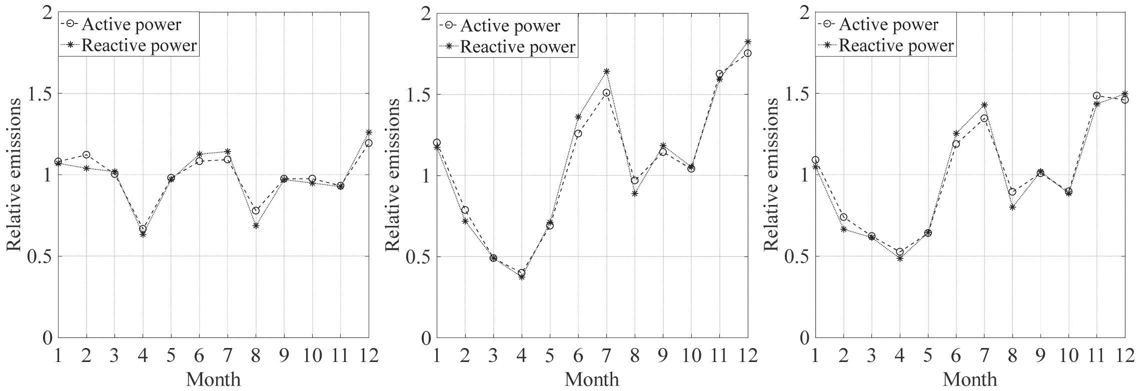
evaluating indicator	NO_2			PM10			PM2.5		
	Standard coal	EP	EQ	Standard coal	EP	EQ	Standard coal	EP	EQ
R^2	0.51	0.69	***0.74***	0.60	0.53	***0.63***	0.64	0.67	***0.74***
NMB	3.88	1.75	-6.79	-3.17	-13.21	-13.73	1.96	-10.3	-10.39
NME	19.71	16.15	15.73	39.96	35.91	35.24	42.08	31.99	29.99

After dividing the 2020 data into two training datasets, spring-winter and summer-autumn, and performing the optimal estimation of their respective electricity consumption data emission coefficients according to equation (2) in [8], the monthly average emissions of NO_2, PM10, and PM2.5 from January 2021 to December 2021 were estimated. The monthly emissions were calculated based on the hourly actual observation values of national monitoring stations as the standard unit value. Calculate the relative emissions predicted based on different levels of activity measurement (coal and active and reactive electricity), as shown in Figure 2.

Evaluate the monthly average prediction results using R^2, NMB, and NME [8]. The average indicators of monthly average predicted results for various pollutants are listed in Table 1.

4.2. Applicability research of enterprise B in the block of Dali

Conduct a comparative study on similar enterprise B in Dali, using the hourly monitoring values of the national monitoring station near enterprise B (2.3km away) from 2020 to 2021 as the actual values, and compare them with the predicted values. Use the 2020 hourly electricity consumption data of enterprise B to iteratively update the emission inventory, and predict the NO2, PM10, and PM2.5 emissions from January 2021 to December 2021. Calculate the relative emissions of each method using the monthly average emissions calculated from the hourly monitoring values of national monitoring stations as the standard unit value, as shown in Figure 3.



(a)NO_2 (b)PM10 (c)PM2.5

Fig. 3. Comparison of Relative Values for Monthly Average Emission Prediction of Various Pollutants (NO_2 (a), PM10 (b), PM2.5 (c))

Evaluate the monthly average prediction results using R^2, NMB, and NME. The average indicators of monthly average predicted results for various pollutants are listed in Table 2

Table 2. Evaluation indicators for monthly average prediction results of pollutant emissions.

evaluating indicator	NO_2		PM10		PM2.5	
	EP	EQ	EP	EQ	EP	EQ
R^2	***0.63***	0.57	***0.51***	0.45	***0.62***	0.56
NMB	-1.68	-2.25	-13.07	-13.18	-10.49	-12.23
NME	11.09	13.16	40.93	43.45	30.57	32.84

4.3. Comparative Analysis

The power IoT based block-level air pollutant emission prediction method proposed in this paper has achieved the best R^2 estimation of reactive power in the scenario of NO_2, PM10, and PM2.5 emission prediction for enterprise A, respectively reaching 0.74, 0.63, and 0.74. The correlation between BJ01 stations in reference [14] is around 0.6~0.7, which is consistent with the estimation results of pollutant emissions of enterprise A using the method presented in this paper. The R^2, NMB, and NME indicators optimized for NO_2, PM10, and PM2.5 in Table 1 of reference [13] are not as effective as the estimation of pollutant emissions of enterprise A using reactive power in this method, reflecting the effectiveness of this method in estimating pollutant emissions of enterprise A.

The predicted results of pollutant emissions from similar enterprise B in Dali have deteriorated compared to the enterprise A, which may be due to:

a. The geographical location and environmental factors of the national monitoring station near Enterprise A and Enterprise B are different, and Enterprise A is located in the main wind direction of the national monitoring station. And Enterprise B is located at the main downdraft of the national monitoring station. Thus, the pollutants emissions of Enterprise A can easily diffuse to national monitoring stations. The pollutants emissions of Enterprise B are not easily diffused to national monitoring stations, which may affect the measurement accuracy of pollutants at national monitoring stations.

b. The average temperature in Yuxi in 2021 was 18.2 ℃, while the average temperature in Dali in 2021 was 16.2 ℃. The average temperature in Yuxi is higher, which is more conducive to the diffusion of air pollutants, thus contributing to the correlation between electricity consumption data and observed air quality.

In addition, why Enterprise A uses reactive power for accurate prediction may be due to the large proportion of reactive power in production electricity related to pollutant emissions. In the production process of such enterprises, a large number of motors are often used to generate inductive reactive power loss, and the use of reactive power can more accurately reflect the pollutant emission characteristics of the enterprise.

5 Conclusion

In this paper, an iterative update framework of air pollutant emission inventory based on statistical methods and regression models is adopted, and a block-level air pollutant emission prediction method based on the power IoT is studied. Based on the block-level real-time electricity consumption data acquired by the power IoT in Dali and Yuxi from 2020 to 2021, experimental research was conducted on the prediction method using hourly air quality historical data from corresponding national monitoring stations to verify its effectiveness, and influencing factors of algorithm applicability is analysed. How to optimize the block-level air pollutant emission prediction method with low computation power requirements proposed in this paper, combining the distributed computing characteristics of the power IoT, meeting the larger scale applications in smart cities, is our next work.

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